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Abstract

In this paper we sketch out a two-way-path from the general definition of collective intelligence to the specific usage of collective intelligence in 'corporate web 2.0' and back again. On the one hand we argue for a better formal underpinning of the connection of micro-level activities and macro-level emergents in the context of collective intelligence. On the other hand we reason that explicit consideration of examples from the web 2.0 in the discussion of collective intelligence will lead to better models of collective intelligence if done systematically. We propose a first step towards a model that could help to understand emergence and individual motivation in collective intelligence systems.

1 Introduction

Collective intelligence is still a relatively new field of research. This can be seen e.g. by looking at the research agenda provided by Malone [17] which includes (1) collecting examples, (2) creation of new examples, (3) systematic studies and experiments and finally (4) theories "to help tie all these things together". Research on collective intelligence today is split within this agenda. On the one hand there are theory-driven approaches [26, 14, 23], mostly inspired by biological swarm intelligence [5], which introduce notions such as emergence, i.e. that the collective is capable of doing what no single individual in it could have done. On the other hand there are example driven approaches mostly inspired by the manifestation of collective intelligence in the web 2.0 [4] which catalogue examples using the 'genome' [18] or characteristics [9] of collective intelligence. These approaches are however not mutually exclusive. Ideally there should be a continuous theoretical path from a general definition as e.g. stated by Malone [17] – "Collective intelligence is groups of individuals doing things collectively that seem intelligent." – to the variety of examples and vice-versa.

This path has yet to be fully described, an end towards which this paper may make only a first step. We concentrate on examples from the web 2.0 since they are well understood in previous work. On from its introduction, the term web 2.0 has been strongly connected to the concept of harnessing collective intelligence [20] so that the web 2.0 is by definition a source for many examples of collective intelligence. The main problem is that the discussion of such examples is agnostic of a formal notion of collective intelligence beyond the level of aforementioned definition. It also often does not take into account that collective intelligence is enabled by computer systems [14], neither on an abstract level as discussed by Heylighen [11] and Lykourentzou et al. [16], nor on the level of implementation as shown in [1]. This however maybe one of the strongest links between collective intelligence and the web 2.0. Stocker et al. [24] discuss corporate web 2.0 in the context of social and technological aspects, highlighting that the web 2.0 is a socio-technical system.

In this we present two central ideas. First that the isolation of collective intelligence properties from examples, be it ‘alleles’ in the genome metaphor or characteristics as presented in [9], may make use of the concept of distinctive features to come to more concise results. Second that the collective activity may be modelled using a Markov Decision Process as to overcome shortcomings of previously described formalisms of collective intelligence. To this end, the paper is structured as follows: In section 2 we review previous research on the properties of collective intelligence with respect to the construction of a continuous path between definition and example. In section 3 we look at a class of examples for collective intelligence systems: the corporate web 2.0. We discuss how examples can reshape the way we think about collective intelligence. In section 4 after we have identified the need to better explain emergence and the motivation of individuals in collective intelligence systems, we propose a model that can be seen as a first step towards a better understanding. The paper is concluded by section 5.

2 Properties of Collective Intelligence

From Definition to Example

The working definition [17] of collective intelligence as stated in the introduction intentionally is very broad. This is because collective intelligence includes phenomena reaching from individuals with very limited capabilities collectively performing relatively complex tasks beyond their own comprehension (e.g. ants and bees) to highly intelligent individuals displaying collective behaviour which is not very much more intelligent than the individuals themselves (e.g. team sports) [11]. The observation of swarm intelligence [5] at the one end of the spectrum has led to the understanding that emergence is a defining property of collective intelligence [23]. The notion of emergence is usually very vague [7] but may be formulated in the following general manner [8]:

“A system exhibits emergence when there are coherent emergents at the macro-level that *dynamically* arise from the interactions between the parts at the micro-level. Such emergents are *novel* w.r.t. the individual parts of the system.”

In the context of collective intelligence, the *‘emergents’* may be problem solving abilities [26], knowledge [14] and the like. With this concept at hand, it can be said that, regardless the perceived overall intelligence of the collective, the degree of emergence in insect societies, that build large hives without any grasp of the concept itself, is much higher than in sport teams, where every individual has very good understanding of the ongoing interactions.

Such top-down research helps to define collective intelligence but it does not help to describe, let alone create it. In contrast, bottom-up research starts by observing phenomena from the domain of web 2.0 applications [4, 18] or, more technical, collective intelligence systems [16] and generalises the findings to characteristics of collective intelligence. Recently, Georgi and Jung [9] synthesised these observations into one model of collective intelligence. In addition, in an attempt to link ideas from different fields, they isolated further characteristics of collective intelligence from the domains of organisation theory and business process management.

Characteristic	Possible Values
Individual Goal	Depending on each individual
Background of Individuals	Experts, Amateurs
Form of input	Instruction, Intellect, Raw Material
Size of contribution	Ranges from small to large
Community Goal	Create, Decide
Form of Cooperation	Collaboration, Competition, Collection
Form of Decision-Making Process	Distributed, Decentralised
Decision Making Process	Groups: Voting, Consensus, Averaging, Prediction Market Individuals: Markets, Social Networks, Final Ballot
Objective of task	Creation of knowledge, designs/descriptions of products/services, physical products. Decision about the correctness of knowledge, the best design/description, the most suitable physical product.
Form of output	Tangible Output, Intangible Output
Basic Collective Intelligence Form	Active System, Passive System
Organisational Pattern	Crowd, Hierarchy
Stakeholders	Initiators, Contributors, Beneficiaries

Table 1: Characteristics describing collective intelligence [9]

Table 1 displays the characteristics of collective intelligence as identified by Georgi and Jung [9]. We will not discuss every characteristic in detail here, as this has extensively been done in related work [4, 9, 18]. For purposes of constructing a path between theory-driven definitions and example-driven characteristics, we believe that it should be investigated how the characteristics map to the micro-level macro-level dichotomy of emergence. To this end, we have reordered the characteristics to roughly fall into four smaller groups: characteristics of the (1) individuals taking part (2) collective and its activities (3) result of the activities and (4) system in which the collective resides. Micro-level activity is characterised naturally by the collective activities in the second group, especially by the form of cooperation and the decision making process. Macro-level emergents in the same way are characterised by the task-centric description of the results in the third group. We have already stated knowledge and problem solving abilities as collective intelligence related examples of emergents. Designs and decision making abilities can be viewed as subcases. However, most importantly, to differentiate emergents from plain results, according to the account of emergence given above, the emergents have to be evaluated with respect to their novelty to the individuals where the individuals are described by the first group of characteristics.

The application of the theoretical concept of emergence to characteristics mostly synthesised from example reveals some room for improvement in the list of characteristics. On the one hand, it is difficult to judge whether ants are “experts” or “amateurs” when it comes to “ant-tasks” but most likely they qualify as experts. Nevertheless the emergent is far beyond their individual capabilities. On the other hand, the emergents produced by a committee of human experts may be only little better that the results they would have produced working individually [11]. Rather than a notion of *expertise* of the individuals with respect to the task domain, what would be needed to evaluate emergence is a notion of the *complexity* of the specific task with respect to the individuals [26]. Along the same lines, the *size of contribution* should probably be defined relative to the task. Emergence seems to be more likely where the individual contribution is only a very small fraction of the task (again think of ants) because this indicates that a larger fraction of the task could not efficiently have been completed by a single individual. Thus the relative size of the contribution is also a statement about the individual capabilities in relation to the task. This is also indicated, but admittedly not proven, by the fact that many examples of collective intelligence require only a small contribution of each individual while the examples where large contributions are required are rare [9]. In terms of emergence it could even be questioned whether these rare examples qualify as collective intelligence at all. In the most extreme case there would be a large pool of tasks together with a bijective mapping of the task to a “collective” of individuals. In this scenario although there is a “collective” involved there is no emergence whatsoever. Or, in terms of the general definition, the “collective does not act collectively”.

3 Socio-Technical Collective Intelligence Systems in the Web 2.0

From Example to Theory

In the previous section we have shown that the set of collective intelligence characteristics is far from being undisputable but also, that application of the concept of emergence may help to identify weaknesses and better understand the role of individual characteristics for the big picture of collective intelligence. In this section we explore the same path in the opposite direction and propose a way in which characteristics gained from example can be evaluated with respect to their suitability to enrich a general theory of collective intelligence.

Collective intelligence research in general lacks a clear understanding of how emergence occurs, i.e. how micro-level activities lead to macro-level emergents. Micro-level activity is typically complex [23] and this makes it difficult to delimit micro-level characteristics which are often interdependent, e.g. it is not trivial, that the individual goals should miraculously align with the community goals. The usage of such interdependent characteristics also makes it hard to apply the model to real-world examples. There is no explanation of how characteristics which are possibly irrelevant for a specific system can be identified and why they should be bothered with. Looking at the above list of characteristics the *“form of decision-making”* characteristic e.g. might not have admissible values in *purely creative* scenarios or, in reverse, if every scenario is assumed to have a decision-making aspect, the differentiation of *community goals* into creation and decision appears to be less sensible. A complete set of characteristics that describes collective intelligence will probably never exist. Moreover if characteristics are added unsystematically, the set of characteristics has the potential to become very large and confusing. A more systematic approach would agglomerate characteristics that only occur together and also concentrate only on relevant characteristics. To identify such characteristics we suggest using what linguists call *distinctive features* [12]. A set of characteristics is called a distinctive feature if it alone can make the distinction between two equivalence classes, here of collective intelligence systems. This definition clearly makes distinctive features relevant. It also groups interrelated characteristics as they never can be distinctive alone. For a set of characteristics f to be a distinctive feature it is necessary, that there either exists a *minimal pair* a, b so that the characteristics of a and b are different if and only if the characteristic is contained in f or, in extension of that concept there exists a set of *contrastive pairs* so that e.g. a and b differ in the features f and g but also there exists a pair c, d that differs only in f and h. It is also necessary that no subset of f is a distinctive feature itself. Together the conditions are sufficient. The use of distinctive features provides a way to derive and organise collective intelligence characteristics from example.

Currently there exist too few well-described examples of collective intelligence systems to form a concise set of contrastive pairs. At the current state-of-the-art, the conception of distinctive features is therefore mainly useful to decide what a valuable characteristic is *not*, i.e. to identify characteristics whose values are coupled to that of another one and therefore can never make a difference without alone without also changing that other characteristic. We illustrate this now with an extensive example. As we have already mentioned the web 2.0 is closely related to “harnessing collective intelligence” [20]. The role of collective intelligence for web 2.0 business models [21] has been discussed in detail by Ickler [13]. More fundamentally, Stocker et al. [24] define *‘corporate web 2.0’* as opposed to non-commercial endeavours such as Wikipedia and private blogs:

“Corporate Web 2.0 can be defined as transformation of the social and technological aspects of the new internet into business, leading to a redesign of existing business processes or even to an evolution of new business models.”

Corporate web 2.0 is built on three pillars: business, social aspects and technology. The first pillar includes the business models and business processes that finally lead to value creation. The latter two define the socio-technical system that serves as a basis and an enabler for value creation. Furthermore, the opportunities for value creation, based on the web 2.0, increase exponentially with increasing focus of the business model on it [24]. Stocker et al. [24] understand the social pillar of corporate web 2.0 as a paradigm shift towards distributed generation of content. In the 1970s the term *‘prosumer’* was coined to illustrate that consumers become involved in the production process, e.g. through the increased customisability of consumer goods. In the context of corporate web 2.0, what is produced is often intangible and not consumed by usage. This situation is better reflected by the notion of *‘produsage’* [6]. Produsers seamlessly move around among different roles as creators and users of content. Another related concept is that of self-organising communities [15]. Self-organisation often occurs together with emergence but they are not the same. By definition of De Wolf and Holvoet [8]:

“… the essence of emergence is the existence of a global behaviour that is novel w.r.t. the constituent parts of the system. The essence of self-organisation is an adaptable behaviour that autonomously acquires and maintains an increased order …”

This raises the question of how self-organisation can be reflected as a characteristic of collective intelligence. Self-organisation is closely related to collective intelligence but it is not one of its inherent properties [23]. While the web 2.0 as a whole can be said to be self-organising, we want to first point out that strict self-organisation may not occur in the context of corporate web 2.0 because as we have discussed above the frame of reference is set and influenced by the company and not by the collective. It might be more fruitful to either use a non-binary characteristic to describe a specific collective intelligence system, e.g. its “degree of self-organisation”, or use a weaker term altogether. Ickler [13] differentiates between collective intelligence of *connected* and collective intelligence of *unconnected* individuals. Connected collectives wherein the individuals are aware of each other will display a tendency to self-organisation whereas unconnected collectives have to rely on an external aggregator to aggregate the results of their independent activities. Since taking this idea into account would basically add a new characteristic to the collective intelligence model of Georgi and Jung [9], following the above discussion it should also be inspected with respect to interdependencies with the existing characteristics. The definition of *decentralized* decision making i.e. many individuals independently making decisions [4] already requires unconnectedness as connections imply dependencies. In contrast, *distributed* decision making, i.e. the agreement of the collective on one common decision is greatly alleviated if the individuals are connected. The *“form of decision-making”* characteristic therefore is not distinctive alone and can be replaced with a new feature that applies to both, creative and decisive tasks.

There is more that collective intelligence research can gain from inspection of the web 2.0. The technological pillar of corporate web 2.0 is discussed by Stocker et al. [24] with a focus on standards and quasi-standards such as AJAX and software for wikis and blogs but without an explicit consideration of collective intelligence technologies. Collective intelligence researchers often leave the discussion of implementation to “practitioners” such as e.g. Alag [1], presumably because the algorithms often are – admittedly innovative – applications of well-known ideas. Despite their limited novelty, analysis of collective intelligence algorithms could turn out to be a missing link in our theoretical path. This can be illustrated e.g. by Google’s “PageRank” algorithm [22]. The algorithm gives a very precise account of how micro-level activities – web-site creators linking to other web-sites – lead to macro-level emergents, in this case a ranking of all web-sites by “quality”. The ranking is previously unknown by the individuals and therefore emergent. Even the notion of quality is emergent in the sense that is an implicit average over the quality criteria applied by the individual users when setting their links. On a more abstract level, the technical aspects of collective intelligence systems have been discussed by Lykourentzou et al. [16]. The differentiation of into active and passive systems as included in the characteristics above stems from their work. PageRank implements a *passive* collective intelligence system, one that does not require action from the individual other than the behaviour the individual would have presented in absence of the system. In this case the behaviour is the creation of websites. In passive systems the individual motivation is almost irrelevant, provided the behaviour remains unchanged but the motivation of the individuals is crucial for *active* collective intelligence systems [16]. This illustrates again the concept of distinctive features. A minimal pair *“basic collective intelligence form”* cannot be provided because a change of this characteristic requires a change of the *“individual goal”.*

4 Understanding Emergence and Individual Motivation

Lessons Learned on the Way

With the concept of distinctive features we have proposed a formalism to inspect the interrelations of different characteristics of collective intelligence with respect to the classification of examples of collective intelligence systems. We have yet to explain the interaction of the different characteristics with respect to creating emergence. In the following we will look at the socio-technical aspects of *active* collective intelligence systems. We develop a model that abstracts away from specific tasks. To understand emergence the model has to account for micro-level activities or *actions* but we say nothing more about the nature of the actions than their effect on the system. To understand motivation we need to account for *individual and community goals*. We start with the discussion of the case of *connected* individuals and then briefly show how it can be extended to *unconnected* individuals. We also only discuss the discrete case here.

Lykourentzou et al. [16] have modelled collective intelligence systems using actions ($\vec{a}$), a system state ($\vec{s}$) and some objectives ($\vec{g}$). They also model the functional dependencies between them, e.g. that the future state is a function of the current state and the actions taken, but say nothing about the specifics of the functions. The semantic background of the model therefore is not very sophisticated. Such background is provided by Heylighen [11]. Technically speaking, collective intelligence is the ability of a collective of agents to transform a system from an initial state into a more desired future state. The state may include long-term results of previous work, so called *stigmergic signals* from the Greek stigma (“mark”) and ergon (“work”), as well as the state of the object which is currently worked on. Heylighen [11] describes the individual’s internal representation of the problem domain as a mental map. The central idea is that every individual has an incomplete and probably inaccurate mental map of the problem but together they can develop an accurate collective mental map by means of averaging, feedback loops and division of labour. The solution to a problem is then a path on that map from some initial state $\vec{s}_1$ to some explicit goal state $\vec{s}_k$. Unfortunately, the model fails to make the difference between the collective mental map and its object, i.e. a “true” representation of the problem. It also does not explain what makes one state more preferable than another and how the individuals can actively influence the state using actions. In produsage scenarios there is no identifiable final state as the artefacts are never finished and always subject to further development [6]. Moreover, making the collective mental map explicit would require that individuals are able to grasp it, something clearly not the case in the presence of emergence.

One line of collective intelligence research models collective intelligence systems by using methods of reinforcement learning [28]. Wolpert and Tumer [28] however are of the opinion that the traditional understanding of reinforcement learning as the solution to a Markov decision process, as described in [25], is insufficient to model collective intelligence because the resulting models typically are simplistic. We want to challenge this opinion on the grounds that Markov decision processes have already been applied in the study of collective actions, e.g. [27], and, in a collective intelligence context, can be seen as a logical extension of the work of Lykourentzou et al. [16]. We will show how the modelling of a collective intelligence system as a Markov decision process may link the abstract notion of a system by Lykourentzou et al. [16] to the semantic background provided by Heylighen [11] at the same time addressing the aforementioned weaknesses of the latter approach. Following quantitative research on social interaction and group utility, we assume that the agents actively pursue both individual and community goals but with varying effort [2]. The agents profit from the community [10] and are also willing to invest for that profit. This pursuit of goals at the same time motivates the individuals to navigate their mental map of the problem and raises an individual preference order over the states. The Markov decision process itself models the underlying "true" system, as opposed to a map of the system, i.e. typically the individuals who are in this context called agents do not know the details of the underlying markov decision process. Building an internal representation of the process from observation is the objective of reinforcement learning. Following reinforcement learning literature [25] we assume that the individual agents seek to maximise their return, a concept which we will soon explain. With all this prerequisites at hand we are set to introduce our model.

A Markov decision process is a 4-tuple (S, A, P, Q_i). S denotes a set of states, i.e. $\vec{s}_t \in S$ is an encoding of the *state* of the system at time t. In connected collective intelligence scenarios the same state is observable by all agents and serves as the collective's shared memory. $A(\vec{s})$ is a set of actions the agents may perform when in state $\vec{s}$. We assume that the agents will agree upon a common action $\vec{a} \in A$ in the connected case. Otherwise the nature of states and actions is dependent on the specific scenario. $P(\vec{s}, \vec{a}, \hat{s})$ models the probability that the state will become $\hat{s}$ if action $\vec{a}$ is taken in state $\vec{s}$ and $Q_i(\vec{s}, \vec{a})$ is the expected reward for agent i for taking action $\vec{a}$ in state $\vec{s}$. Note that in the original Markov decision process there is only one agent and consequently only one reward function. Rewards may be negative. The agents get rewarded for a state transition i.e. the transformation from a state $\vec{s}$ to another state $\hat{s}$ by some action $\vec{a}$. We call the reward of agent i for such a transition r_i. Q_i then becomes the expected value over all future states with respect to P, i.e.

$$Q_i(\vec{s}, \vec{a}) = \sum_{\hat{s} \in S} P(\vec{s}, \vec{a}, \hat{s})\, r_i(\vec{s}, \vec{a}, \hat{s}) \tag{1}$$

To define r_i we recall that the overall objective is to transform the system into a more desirable state than the status quo. It is now the question what makes one state more desirable than another. In principle this can only be answered individually since preferences may vary for every agent. Following the discussion at the beginning of this section, let $\vec{g}_{Ii}$ and $\vec{g}_{Ci}$ be an encoding of the individual and collective goals of agent i in. Agent i's judgment of a state $\vec{s}$ may now be expressed by some objective function:

$$\Gamma_i(\vec{s}) = f(\vec{g}_{Ii}, \vec{g}_{Ci}, \vec{s}) \tag{2}$$

The system goes through a series of states $(\vec{s}_t, \vec{s}_{t+1}, \ldots, \vec{s}_T)$ over time. This is called a markov chain. Let $c_i(\vec{a})$ be the costs for agent i to perform action $\vec{a}$. We define the reward of the transformation from $\vec{s}_{t-1}$ to $\vec{s}_t$ by taking action $\vec{a}$ as the subjective improvement of the state minus the costs of that improvement. The reward of agent i at timestep t is given by

$$r_{i,t} = \Gamma_i(\vec{s}_t) - \Gamma_i(\vec{s}_{t-1}) - c_i(\vec{a}_t) \tag{3}$$

The last question is how to determine what action to take given a state. It is well known that the greedy strategy, i.e. the maximisation of the immediate reward can be suboptimal, e.g. when it leads to a state from which there is no path to the optimal state. It is therefore assumed that the agents maximise the sum of their rewards, which is called the return R_i.

By insertion it can be seen that return of a finite path from an initial state s_1 to a goal state s_k is

$$R_i = \Gamma_i(\vec{s}_k) - \Gamma_i(\vec{s}_1) - \sum_{t=1}^{k} c_i(\vec{a}_t) \quad (4)$$

Produsage, i.e. continuous improvement of the status-quo over virtually infinite time, would lead to an infinite return. This situation can be modelled using the discounted return $R_{i,t}$ at a given time t. The idea is that an agent at time t will value the immediate reward she gets higher than rewards in the future. The discounted reward is defined as

$$R_{i,t} = \sum_{j=0}^{k} \gamma^j r_{i,t+j+1} \quad (5)$$

where $\gamma < 1$ is the discount factor and $\gamma = 0$ would model a greedy agent.

The case of unconnected individuals can be modelled using a decentralised markov decision process [3]. Without going into too much detail we present the basic ideas. Since the agents are unconnected, they can no longer agree upon a common action but act individually so that for n agents the action set is redefined as the set of joint actions $A = A_1 \times \ldots \times A_n$ where $A_i(\vec{s})$ is the set of actions that can be taken by agent i in state $\vec{s}$. P and Q_i have to be redefined accordingly. The agents may also no longer observe the full state in the unconnected case; otherwise the state would be an implicit connection. The joint set of observations is $\Omega = \Omega_1 \times \ldots \times \Omega_n$. The observation function

$$O\big(\vec{s}, (\vec{a}_1, \ldots, \vec{a}_n), \hat{s}, (\vec{o}_1, \ldots, \vec{o}_n)\big) \quad (6)$$

indicates the probability of the agents making the joint observation $(\vec{o}_1, \ldots, \vec{o}_n) \in \Omega$ when taking the joint action $(\vec{a}_1, \ldots, \vec{a}_n) \in A$ in state $\vec{s}$ and thereby arrive at state $\hat{s}$. The joint observation should fully determine the state, i.e.

$$O\big(\vec{s}, (\vec{a}_1, \ldots, \vec{a}_n), \hat{s}, (\vec{o}_1, \ldots, \vec{o}_n)\big) > 0 \Rightarrow P\big(\hat{s} \big| (\vec{o}_1, \ldots, \vec{o}_n)\big) = 1 \quad (7)$$

To solve decentralised markov decision processes, different methods than for the centralised case are required but in terms of collective intelligence, the same considerations can be applied.

While previous models where only vague about state transitions and the choice of actions by using a Markov decision process we are able to make precise statements about the transitions using a probability function and make the choice of optimal actions accessible to the established theory of reinforcement learning. This also is the key to differentiate between the actual problem and the agent's internal representation of it. Furthermore, the model better fits into the semantic background. We have discussed the semantics of states and actions in connected and unconnected scenarios. We also can account for the fact that most real-life scenarios are not deterministic. In scenarios with a defined final state we go beyond previous models by requiring a cost-efficient solution. In equation (4) the initial and final states are identical for every path so that maximising the return equals finding a series of cost-minimal actions. Scenarios which continue indefinitely were not even possible previously. Our model allows agents to navigate on a not explicitly known collective mental map, a true sign of emergence. In both, connected and unconnected scenarios agents can explicitly determine their preferred action in a given state. This is entirely a micro-level activity based only on the observation of the current state and the possible actions. The agents' assumptions about the other states and the associated rewards may be incomplete or inaccurate. The actions are aggregated still on micro-level to one action either by joining them or by using one of the many methods mentioned in this paper. Emergence occurs only through the effect of the combined action. This greatly reduces the effort of applying the model to a specific system because emergence has not to be modelled again for every system. We also reduced the effort to model individual motivation to defining function f from equation (2).

5 Conclusion and Further Work

There has already much been written on the phenomenon of collective intelligence and its manifestations, be it w.r.t. human motivation, business models, or technical solutions, respectively. With this paper, we intent to take the next step in the research process and conceptualise the example-based knowledge that has been gathered so far. The potential of the "many" working together and creating new ideas or knowledge is obviously especially interesting for business, i.e. profit creating, purposes. To analyse emergence on the one hand and the motivation to create value-added results on the other hand, defining characteristics of collective intelligence have to be derived systematically, rather than arbitrarily. This can be done by using the concept of distinctive features. To furthermore understand the mechanisms within an active collective intelligence system Markov decision processes can be used to model how agents pursuit individual and community goals. With this a systematic conceptualisation process has been initiated, but of course further research has to be done. With our model, once we understand the origination and development of the different types of motivation, we already have a place where to "plug-in" these findings into the model of collective intelligence systems: the objective function. Out model translates the objective function into a reward function based on the relative preference of states thereby offering a direct explanation of how the objective function influences the behaviour of the collective intelligence system. Nevertheless we are aware that this is only part of the answer, especially if collective intelligence systems are viewed as complex socio-technical systems as their connection to the web 2.0 suggests. We will examine this point in subsequent work. Furthermore, the reciprocal effects between the technological platform and the quality of interactions, i.e. the quality of the results, are worth to be examined. Last, but not least, we have to understand the degree of automation that is desirable to render the production of collective intelligence efficient. Here again the careful examination of examples using distinctive features will be helpful.

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